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Localization of Passive RFID tags with Robot using Adaptive Likelihood Distribution Algorithm

Yuuki Ota†, Toshihiro Hori†, Taiki Onishi†, Tomotaka Wada †, Kouichi Mutsuura‡, Hiromi Okada†
†Faculty of Engineering, Kansai University, 3-3-35 Yamate-cho, Suita-shi, Osaka 564-8680 Japan
‡Faculty of Economics, Shinshu University, 3-1-1 Asahi, Matsumoto-shi, Nagano 390-8621 Japan
Email: {ota, hori, wada, okada}@jnet.densi.kansai-u.ac.jp, mutsuur@shinshu-u.ac.jp

***Abstract-* The RFID (Radio Frequency IDentification) tag is expected as a tool of localization. By the localization of RFID tags, a mobile robot which installs in RFID readers can recognize surrounding environments. In addition, it can be applied to a navigation system for walkers. In this paper, we propose an adaptive likelihood distribution scheme for the localization of RFID tags. This method adjusts the likelihood distribution depending on the signal intensity from RFID tags. We carry out the performance evaluation of estimated position error by both computer simulations and implemental experiments.**

Keywords- RFID reader, RFID tag, localization, likelihood distribution, estimated position error

I. Introduction

In ubiquitous society, all electric components, and devices include computers connected to the networks. When users need some information, they distinguish what an individual thing is and obtain necessary information from the networks based on the identification information. RFID attracts attention as an identification source. RFID system consists of RFID reader/writers and RFID tags. The RFID tags have unique identifiers. In this paper, we focus on the RFID reader for detecting the positions of RFID tags. The RFID reader reads the ID of the RFID tag from the received signal.

An RFID reader can detect the received signal from RFID tags, when the tags exist close to the RFID reader. This detected signal is called contiguous information [1]. We can know approximate positions of the tags from the contiguous information. Using successive contiguous information of the tags, we can establish more precise localization. However, the readable distance of the tag varies with conditions such as environments between the RFID reader and tags or allocations such as positions and degrees of tilted tags. The precision of this method is not so effective [2].

The localization methods of RFID tags based on the Bayesian estimation have been proposed in [3]-[5]. The RFID reader observes RFID tags from plural locations. So, precise estimations of the tag positions are enabled. In addition, it is hard to be affected by environment. However, these conventional methods use the fixed likelihood distribution regardless of RFID tag location. Since we have to observe the tag from various locations of the RFID reader, it is necessary for the RFID reader to move for a long distance. In other words, it takes a long time to estimate a accurate position of a tag. In practical use, because there is a limit for movement of an RFID reader, the locations where the RFID reader can observe the tag are so restricted.

In this paper, we propose an adaptive likelihood distribution scheme to solve this problem. This scheme adjusts the likelihood distribution depending on the signal intensity from tags. The signal intensity varies with positions and angles of tags [6]. If a tag is very close to a RFID reader, the signal intensity from the tag becomes high. When the value of likelihood distribution is high, the tag may exist in the vicinity of the RFID reader. In the proposed scheme, we show that the proposed scheme makes it possible to estimate a more accurate position of tags than the conventional scheme.

This paper is organized as follows. In section 2, the conventional method of localization of RFID tags is discussed. In section 3, we propose an adaptive likelihood distribution scheme. Section 4 presents the performance evaluation of estimated position error by implemental experiments. Section 5 presents the performance evaluation by computer simulations. Finally we conclude this paper in section 6.

II. Conventional method of localization

The previous paper [3] estimates the posterior probability $p(x|z_{1:t}, r_{1:t})$ for decision of tag positions. In this posterior probability, x is the positions of the tags, $z_{1:t}$ are the observations of the tags at time step from 1 to t, and $r_{1:t}$ are locations of the RFID reader at time step from 1 to t. Based on the Bayesian estimation, the following equation is defined.

$$p(x|z_{1:t}, r_{1:t}) \propto p(z_t|x, r_t)\, p(x|z_{1:t-1}, r_{1:t-1}) \qquad (1)$$

Here, $p(z_t|x, r_t)$ expresses the likelihood of observation z_t given the position x of the tag and the location r_t of the RFID reader. It is assumed that the likelihood depends on only the relative positions between the tag and the RFID reader.

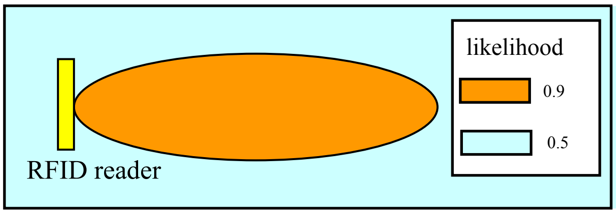

Fig.1 Fixed likelihood distribution model

Fig. 1 shows the fixed likelihood distribution model. The detection range of the RFID reader is assumed to be ellipse from the directivity of the RFID reader. For a simple model of detecting tags, we set the likelihood of this range as 0.9, and that of outside range as 0.5.

Next, the paper [3] shows the procedure of localization of tags. Fig. 2 shows a flow chart of localization. To represent the posterior probability for the location of an RFID tag, the model uses virtual positions (VPs) in a reticular pattern. If an RFID reader detects a tag first time, the paper assumes VPs with uniformity in a circle of 3m radius around the position of the RFID reader. The method assigns the posterior probability $p(x|z_{1:t}, r_{1:t})$ to each VP. The method assigns the value of likelihood with the fixed likelihood distribution. In eq. (1), the posterior probability of each VP is updated according to the likelihood. Whenever the RFID reader detects the tag, the posterior probability is updated according to eq. (1). If there are plural VPs that have the largest probability, the paper assumes that the center of gravity of the VPs area is the estimated position of the tag.

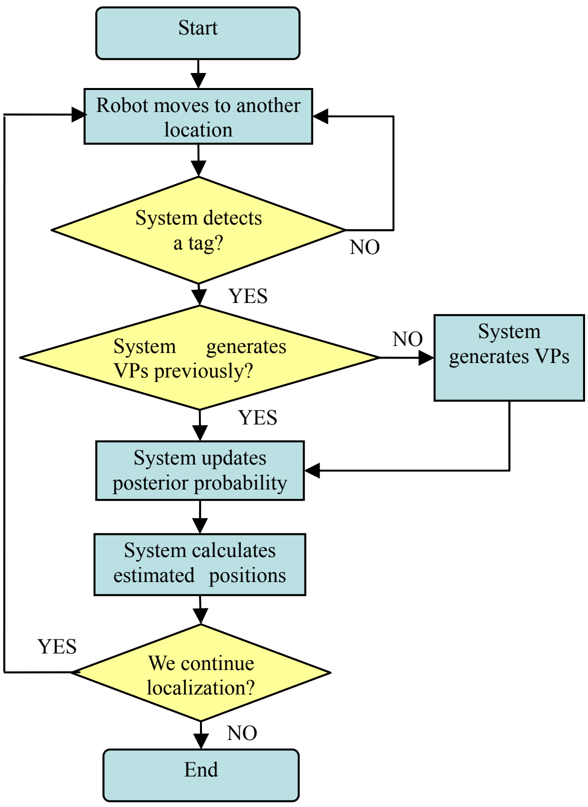

Fig.2 Flow chart of localization

Fig. 3 shows an example of updating the posterior probability at time step 1. Here, we consider that a robot installed with RFID readers moves, looks for tags, and makes the localization of the tags. It is assumed that an RFID reader detects a tag to time step 1 in the first time. The paper generates VPs and assign the likelihood by the fixed likelihood distribution. The probabilities of VPs that plot with triangle markers are calculated by (prior probability 1)*(likelihood 0.9) =0.9. The probabilities of VPs that plot with circular markers are calculated by (prior probability 1)*(likelihood 0.5) =0.5. Then, the robot moves a little and repeats the procedure.

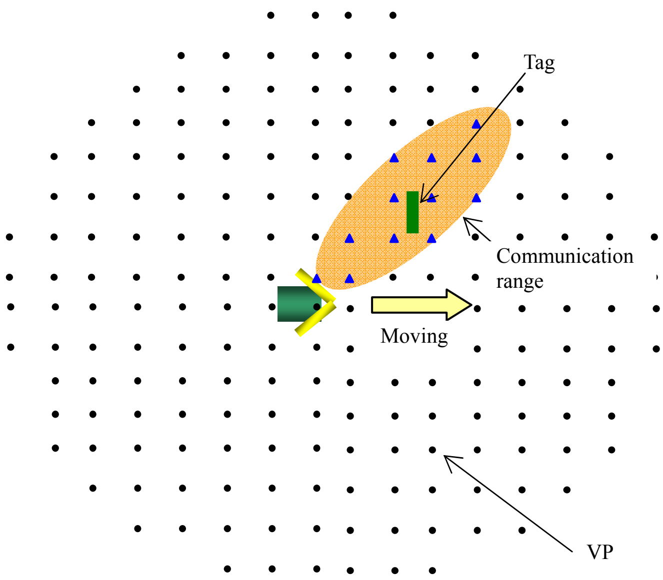

Fig.3 Update of posterior probability at time step 1

III. Adaptive likelihood distribution

The conventional method uses the fixed likelihood distribution regardless of the position of the tag in section 2. However, we can know a position of the tag more precisely when we measure the signal intensity from the tag. We propose an adaptive likelihood distribution that takes the signal intensity from the tag into account. Fig. 4 shows the proposed adaptive likelihood distribution model.

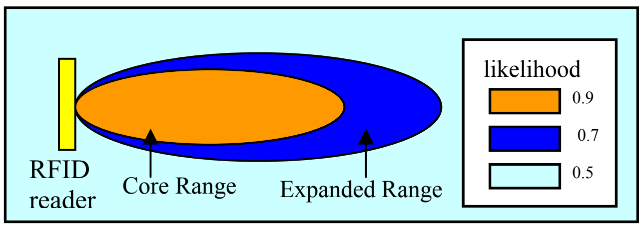

Fig.4 Adaptive likelihood distribution model

The adaptive likelihood distribution consists of three areas. The first is Core Range that is the major detection range of the RFID reader. The size of Core Range is determined by the signal intensity from the tag. The likelihood of Core Range is the highest in this likelihood distribution model. The second is Expanded Range that may detect a tag by a reflection from neighboring environment. We assume the likelihood of Expanded Range is less than that of Core Range. So we set the likelihood of Expanded Range as 0.7. The third is the area outside of these two ranges. We set the likelihood of 0.5 since the distance between RFID reader and tags is larger in this area than that in other two areas.

Next, we describe Core Range and Expanded Range in detail, respectively.

A. Core Range

We normalize the signal intensity to a range of 0 to 1. We define this as the signal intensity level α. With this α, we calculate the maximal distance from the RFID reader to the tag. We define the distance as Calculation Distance (CD) and show it in eq. (2).

$$CD = \frac{1}{\sqrt[4]{\alpha}} \qquad (2)$$

In addition, we define Redundant Distance (RD) in consideration of a reflection from neighboring obstacles. RD is a value to make the CD a little larger. RD is used for not sensitive in Core Range to position of tags. We show RD in eq. (3).

$$RD = CD \times 0.2 \qquad (3)$$

We define a major axis of Core Range as CD+RD. In addition, we define a minor axis as $(CD + RD) \times (7/20)$. 7/20 is the ratio of a major axis and a minor axis determined by the experiments. We show the details of the Core Range in Fig. 5.

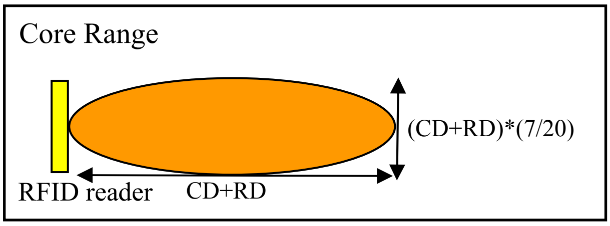

Fig.5 Core Range

B. Expanded Range

The probability that the tag exists in Core Range is the highest in that of all areas. However, the signal intensity may be strengthened under the influence of some reflection from surrounding obstacles. So, the tag may exist outside Core Range with small probability. We consider Expanded Range where there may be a tag at this possibility.

Expanded Range is considered to have a wider communication range than Core Range. We consider that Expanded Range has the ellipse shape in Fig. 1 as well as Core Range. In addition, the likelihood of Expanded Range is lower than that of Core Range.

C. Adaptation of Core Range

Core Range varies according to the signal intensity. Core Range is small when the signal level α is high. We show the likelihood distribution when α is high in Fig. 6. When the intensity is high, it is very likely that there is a tag near the RFID reader.

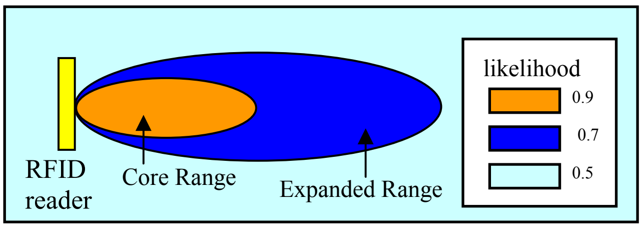

Fig.6 Adaptive likelihood distribution model (α is high)

On the other hand, Core Range is large when the signal intensity level α is low. We show the likelihood distribution when α is low in Fig. 7. When the signal intensity is low, a tag may be far from the RFID reader. In addition, the signal intensity may go down even if there is a tag near the RFID reader.

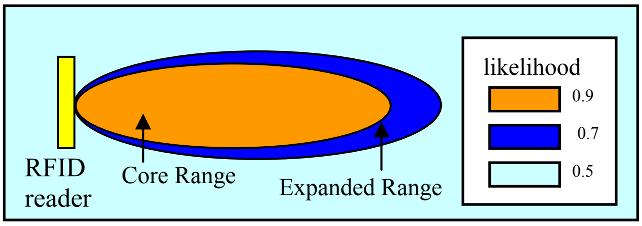

Fig.7 Adaptive likelihood distribution model (α is low)

IV. Performance evaluation by implemental experiments

A. Performance evaluation of communication range

We carry out the performance evaluation by implemental experiments to show the effectiveness of the proposed method. We use the RFID system of 2.45GHz (SHARP Corporation: RZ-2TG1, RZ-1TG4).

At first we examine the communication range of the RFID reader. Fig. 8 shows the relationship between the RFID reader and tags. When the RFID reader and the tag are paralleled or vertical, we describe it as parallel or vertical, respectively. We show the communication range when the tag is parallel to the RFID reader in Fig. 9. We also show the communication range when the tag is vertical to the RFID reader in Fig. 9. The RFID reader exists in (0, 0).

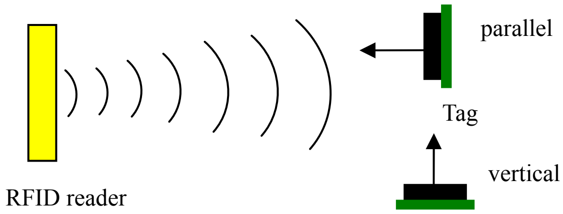

Fig.8 Relationship between an RFID reader and tags

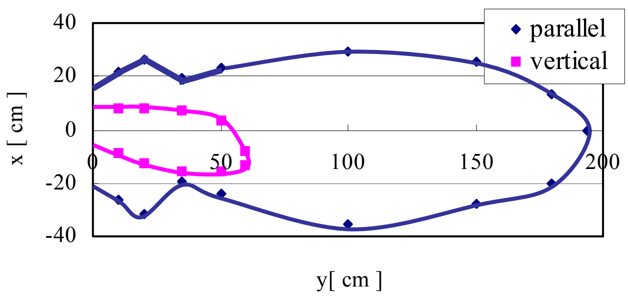

Fig.9 Communication range of an RFID reader

When the tag is parallel to the RFID reader, the communication range becomes so wide. However, the communication range shrinks by a degree of leaning of the tag. In addition, the side robes are observed in the vicinity of the RFID reader.

B. Performance evaluation of localization

In this paper, we assume a mobile robot that installs two RFID readers as shown in Fig. 10. The robot has RFID readers to right and left with 45 degrees from a progress direction.

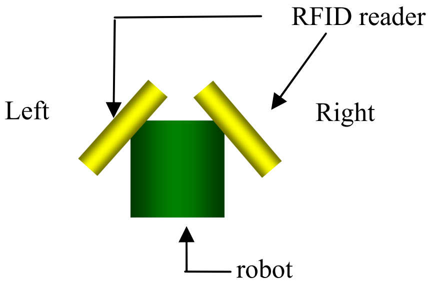

Fig.10 Mobile robot

In the proposed method, we need to measure the signal intensity from a tag, in order to obtain the adaptive likelihood distribution. Here, instead of measuring the signal intensity level, we change four kinds of communication distances of tags. To decide Core Range, we investigate whether the RFID reader can detect the tag or not in four kinds of communication distances such as 70cm, 100cm, 140cm, and 200cm. Then, we settle the signal intensity level according to the results. For example, when the RFID reader can detect the tag in the communication distances of 200cm and 140cm, we set CD as 140cm and decide Core Range by eq. (3).

Fig. 11 shows the mobility of the robot that moves between point A and B. The robot starts from the point A to the point B. When it reaches the point B, it turns over and goes back to the point A.

We consider four cases of distances, say L, between the tag and the moving line of the RFID reader. Those distances are 20cm, 40cm, 80cm and 100cm. Table 1 shows parameters of experiments. In addition, we carry out experiments in the environment without any obstacles and the environment where we put a tag above a metallic desk. When we assume the environment that a metallic desk exists, the tag contacts with a plastic bottle on the desk.

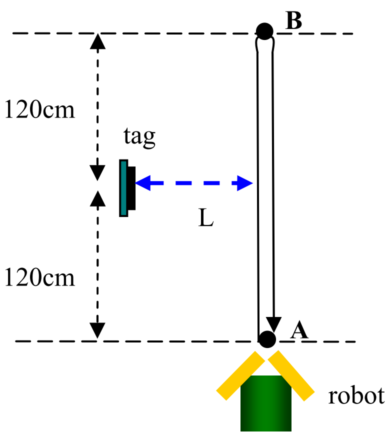

Fig.11 Relation of mobile robot and tag

Table 1 Parameters of experiments

Number of tag	1
Detection interval of RFID reader	10cm/s
Placement pattern of VPs	Grid of 1cm
Communication distances	70cm, 100cm 140cm, 200cm

We show the experimental results from Figs. 12 to 18. The horizontal and vertical axes show the moving distance of the robot and the estimated position error, respectively. Fig. 12 shows the experimental result of L=20cm without any obstacles. We can reduce the estimated error of the proposed method drastically comparing with the conventional one until the robot turns over and the RFID reader detects the tag at 320cm. About 45cm of estimated position errors are reduced by the proposed method. The proposed method can reduce estimated position errors for smaller moving distances than the fixed likelihood distribution. After the robot turns over, both methods have almost the same value of the estimated position errors.

Fig. 13 shows the experimental result of L=40cm without any obstacles. As in the case of L=20cm, the performance of the proposed method is good till the robot turns over and RFID reader detects the tag. About 25cm of estimated position error is reduced by the proposed method. After the robot turns over and the RFID reader detects the tag, both methods don’t have so large difference. However, as for the both methods, the precision is not so good under the influence of side robes of communication range that we showed in Fig. 9.

Fig. 14 shows the experimental result of L=40cm in the case that the tag is above the metallic desk. As the case of L=40cm without any obstacles, the estimated position errors of the proposed method can be reduced till the robot turn over and the RFID reader detects the tag at 310cm. About 40cm of estimated position errors are reduced by the proposed method. After the robot turns over and the RFID reader detects the tag, both methods don’t have so large difference. However, the error with the metallic desk is smaller than that without the one in the proposed method. The signal intensity is strengthened by the reflection from the metallic desk. Because Core Range is reduced, the estimated position of the tag approaches to that of the RFID reader. As a result, the position error becomes low.

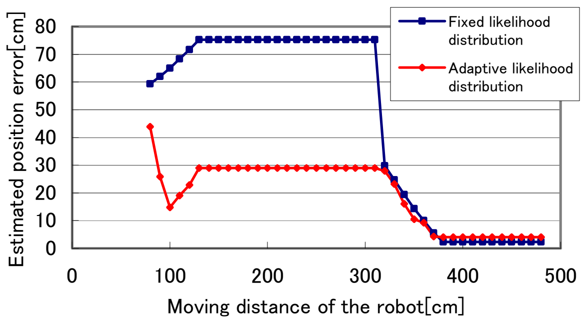

Fig.12 Estimated position error vs. moving distance of robot L=20cm (without any obstacles)

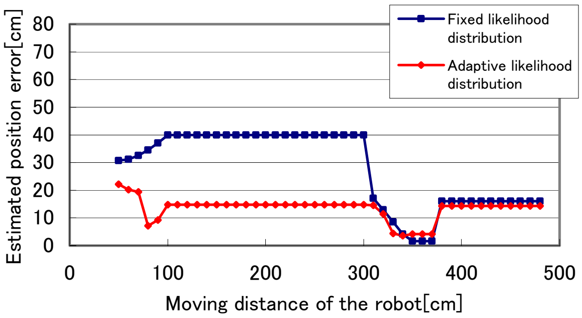

Fig.13 Estimated position error vs. moving distance of robot L=40cm (without any obstacles)

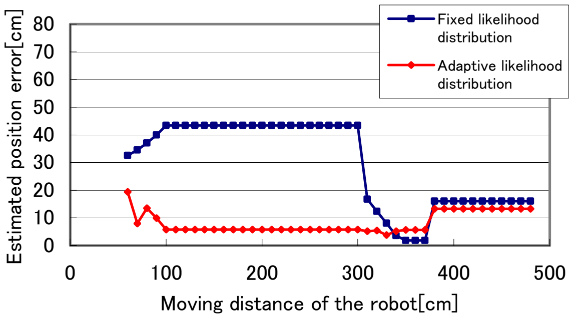

Fig.14 Estimated position error vs. moving distance of robot L=40cm (Tag above the metallic desk)

Fig. 15 shows the experimental result of L=80cm without any obstacles. The proposed method is not so good till the robot turn over and detects the tag at 280cm. About 3cm errors are increased by the proposed method. Because Core Range is reduced until the robot turn over, the estimated position of the tag approaches to that of the RFID reader. As a result, the error becomes so high. However, the errors of both methods don't have so large difference. After the robot turned over and the RFID reader detects the tag, both methods have the same performance.

Fig. 16 shows the experimental result of L=80cm in the case that the tag is above the metallic desk. As in the case of L=80cm without any obstacles, the proposed method is not so good till the robot turn over and the RFID reader detects the tag at 280cm. About 6cm errors are increased by the proposed method. This is because the signal intensity is strengthened by the reflection from the desk. Because Core Range is reduced by the large signal intensity, the estimated position of the tag approaches to that of the RFID reader. As the result, the error becomes so high. However, after the robot turns over and the RFID reader detects the tag, both methods don't have any difference.

Fig. 17 shows the experimental result of L=100cm in the case without any obstacles. The proposed and conventional methods don't have any difference, since Core Range becomes the largest size. As a result, the position error of the adaptive likelihood distribution becomes almost equal to that of the fixed likelihood distribution.

As a result, when L is small, the proposed method shows good performance than the fixed likelihood distribution. When the tag is near to the robot, the signal intensity becomes strong. Since Core Range becomes a small area, the deference between Core Range and Expanded Range becomes large. It is thought that the estimation position error can be small in short moving distance of the robot. On the contrary, Core Range grows big when L is big so that signal intensity becomes weak. Since Core Range becomes a large area, the deference between Core Range and Expanded Range becomes small. Therefore the difference of the performance with the proposed method and the fixed likelihood distribution becomes small. In addition, the proposed method worsens performance in Fig.15, 16. This is so that there is the position of the real tag near a center of gravity of the fixed likelihood distribution.

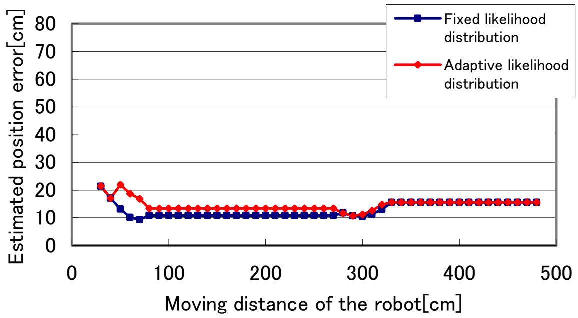

Fig.15 Estimated position error vs. moving distance of robot L=80cm (without any obstacles)

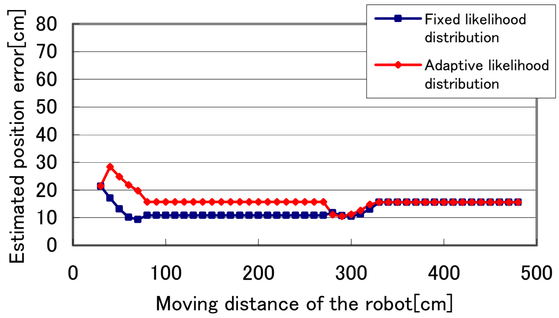

Fig.16 Estimated position error vs. moving distance of robot L=80cm (Tag above the metallic desk)

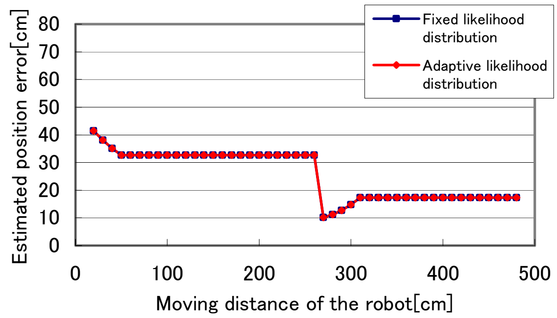

Fig.17 Estimated position error vs. moving distance of robot L=100cm (without any obstacles)

V. Performance evaluation by computer simulations

In section 4, we show the experimental results when the robot moves in a narrow room. As a result, when the robot is pretty closed to a tag, the proposed method is considerably effective for estimating the position of the tag. When the distance L is large, the proposed method is not so good. The differences of the estimation errors between the conventional and the proposed methods are small. In addition, the signal intensity from the tag becomes high by the influence of the metallic desk. However, we show that the proposed method is effective in that environment. In these experiments, the movement of the robot and the number of the observation times are limited.

We carry out the performance evaluation in large-scale office environment by computer simulations. In the simulation, the movement of the robot is complicated and the observation times are large. We show parameters of simulations in table 2 and large-scale office environment model in Fig.18. The moving speed of the robot is 0.2m/sec. The moving direction of the robot is between current progress direction ±15 degrees every 1sec at random. The robot moves along the passage.

Table 2 Parameters of simulations

Number of tags	100
Area	16m×16m
Passage width	2m
Speed of Robot	0.2m/sec
Detection frequency of RFID reader	1Hz
Placement pattern of VPs	Grid of 1cm

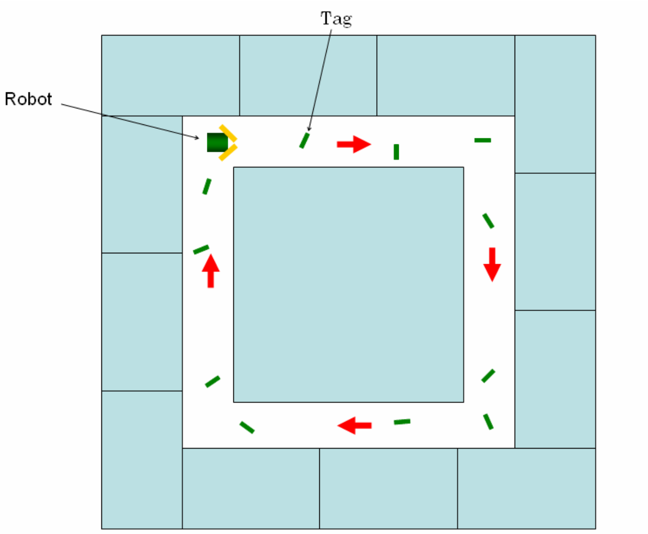

Fig.18 Large-scale office environment model

Fig. 19 shows the simulation result when the placement pattern of VPs is grid of 1cm. In the case of the same moving distance of the robot, the error of the proposed method is smaller than that of the conventional method. By the proposed method, we can reduce the error of 3 to 5cm. In other words, the proposed method can reduce moving distance which is needed to estimate the position of a tag. So, the quick localization is enabled. In addition, we can make the error so small to 2cm by the proposed method when the robot moves 1000cm.

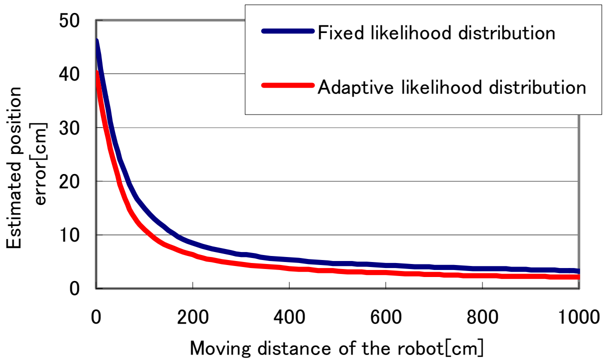

Fig.19 Estimated position error vs. moving distance of robot (VP's grid of 1cm)

VI. Conclusions

This paper has dealt with the localization of RFID tags. We have assumed the situation that some mobile entities like robots installed RFID readers try to acquire the positions of RFID tags. We have proposed an adaptive likelihood distribution scheme to adjust the likelihood distribution depending on the strength of the received signal intensity from RFID tags. When an RFID reader is close to a tag in particular, we have shown that the proposed method is considerably effective for the performance evaluations of estimated position errors in implemental experiments. Moreover, the proposed method is effective even if there are some reflections from neighboring environment. By computer simulations, we have shown that the proposed method is effective even if the robot takes complicated movement in large-scale space. We will apply this method to the three-dimensional space as a future work.

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